Journal of Hydrology 556 (2018) 359–370

Contents lists available at ScienceDirect

Journal of Hydrology

journal homepage: www.elsevier.com/locate/jhydrol

Research papers

Effects of climate change on streamflow extremes and implications for reservoir inflow in the United States

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ARTICLE INFO

Article history:
Received 8 August 2017
Received in revised form 6 November 2017
Accepted 14 November 2017
Available online 15 November 2017
This manuscript was handled by Marco Borga, Editor-in-Chief, with the assistance of Kelly Kibler, Associate Editor

Keywords:
VIC
RegCM4
Streamflow extremes
Reservoirs

ABSTRACT

The magnitude and frequency of hydrometeorological extremes are expected to increase in the conterminous United States (CONUS) over the rest of this century, and their increase will significantly impact water resource management. In this study, we evaluated the large-scale climate change effects on extreme hydrological events and their implications for reservoir inflows in 138 headwater subbasins located upstream of reservoirs across CONUS using the Variable Infiltration Capacity (VIC) hydrologic model. The VIC model was forced with a 10-member ensemble of global circulation models under the Representative Concentration Pathway 8.5 that were dynamically downscaled using a regional climate model (RegCM4) and bias-corrected to 1/24° grid cell resolution. Four commonly used indices, including mean annual flow, annual center timing, 100-year daily high streamflow, and 10-year 7-day average low streamflow were used for evaluation. The results projected an increase in the high streamflow by 44% for a majority of subbasins upstream of flood control reservoirs in the central United States (US) and a decrease in the low streamflow by 11% for subbasins upstream of hydropower reservoirs across the western US. In the eastern US, frequencies of both high and low streamflow were projected to increase in the majority of subbasins upstream of both hydropower and flood control reservoirs. Increased frequencies of both high and low streamflow events can potentially make reservoirs across CONUS more vulnerable to future climate conditions. This study estimates reservoir inflow changes over the next several decades, which can be used to optimize water supply management downstream.

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1. Introduction

Over the past few decades, extreme hydrological events have been increasing across most of the conterminous US (CONUS) (Ahn and Palmer, 2015; Peterson et al., 2008; Novotny and Stefan, 2007; Burns et al., 2007; Kunkel et al., 1999; Karl and Knight, 1998). However, these trends vary by region. Some areas, such as the Southwest, have experienced prolonged droughts (Cook et al., 2015), whereas regions in the central US have experienced an increase in the frequency of heavy precipitation (Pryor et al., 2009). Areas in the eastern US have also observed an increase in the frequency of heavy precipitation and streamflow events (Groisman et al., 2001).

With expected increase in the frequency and duration of both wet and dry extreme events (Singh et al., 2013; Touma et al., 2015; Pagán et al., 2016), it will be more challenging to optimally manage reservoirs to meet all competing objectives. For example, in arid regions, increased drought duration and severity may result in an inability to maintain minimum release rates for the reservoirs. On the other hand, increases in precipitation could cause reservoirs to store more water, but they could also lead to uncontrolled water releases and cause downstream damage (Carlton and Kandathil, 2013). Increases or decreases in mean annual precipitation and the resulting changes in runoff can affect downstream reservoir operations and impact recreational activities, water quality, and stream and shoreline ecosystems. Therefore, a better understanding of streamflow variation in the upstream areas of

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https://doi.org/10.1016/j.jhydrol.2017.11.027
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reservoirs is necessary to improve future reservoir operations and watershed management.

Recent studies have examined how the changes of historic and future hydrologic conditions may affect large and regulated river systems (Zhou et al., 2016; Haddeland et al., 2014; Biemans et al., 2011; Döll et al., 2009; Hanasaki et al., 2006; Christensen and Lettenmaier, 2007; Hamlet and Lettenmaier, 1999; Hamlet et al., 2010). Using large-scale hydrologic models with reservoir operation simulated at selected major dams, these studies provided high-level evaluation and suggested significant impacts in some major river basins. However, considering the complexity of existing water infrastructure systems, the actual impacts can be far more complicated. In the US alone, there are over 88,000 dams ranging from a wide variety of sizes to support various objectives (USACE, 2017), including flood control, municipal water supply, irrigation, hydropower generation, and aquatic wildlife protection. Their site-specific impacts, from a single project to an integrated system, may not be fully depicted through large-scale hydrologic models. A refined modeling framework will eventually be required to provide more locally relevant information (Wood et al., 2011; Bierkens et al., 2015).

To gain an overall understanding of the possible site-specific climate change impacts on various reservoirs across the CONUS, we present a spatially consistent methodology for analyzing climate change impacts, with a particular focus on hydrological extremes and their implications for reservoir inflows. Using a hydrologic model implemented at 1/24° (~4 km) grid resolution over the CONUS (Oubeidillah et al., 2014), this study aims to draw a comprehensive picture of conceivable changes in extreme flow events in multiple headwater subbasins across the CONUS, where historic streamflow observation is available to support model validation. Although we did not account for water management effects on hydrological responses in downstream areas, understanding future changes in reservoir inflow—such as the magnitude and timing of extreme events in headwater basins—is important for water resource management (e.g., Alexander et al., 2007). Therefore, this work should enhance the scientific understanding of changes in local hydrological patterns nested within large river basins and offer baseline information for adaptive water resource management in a changing climate. Specifically, this research addresses two questions: (1) How will near-term hydroclimate changes affect the volume and timing of both low and high flows in catchments upstream of reservoirs? (2) What types of reservoirs and water resource regions across the CONUS will be more vulnerable to future climate conditions?

Section 2 of this paper describes the downscaled climate change projections, hydrologic simulations, and the data used for the analyses. Section 3 focuses on the evaluation of the hydrologic modeling, the effects of hydroclimate changes on the volume and timing of inflows, hydrological extremes, and the implications for reservoir inflows. The conclusions are summarized in Section 4.

2. Methods and data

2.1. Selection of reservoirs and gauge stations

To investigate the effects of climate change on reservoir inflows across the CONUS, and to identify signals induced by climate change, we selected multiple analyzable pairs of reservoirs and gauge stations that (1) are mostly unregulated and have minimum human influence, (2) have sufficient historic streamflow observations (i.e., at least 10 years of records between 1981 and 2012) for model validation, and (3) possess an upstream drainage area greater than 100 km^2. This selection criterion allowed us to identify signals that were mainly caused by climate change. However, we recognize that such an approach does not account for any hydrologic changes resulting from climate change driven land cover variations or other human activities (e.g., land use, dam regulation, and flow diversion). Identification of unregulated gauge stations was based on the United States Geological Survey (USGS) Geospatial Attributes of Gauges for Evaluating Streamflow (GAGES-II) database (Falcone et al., 2010; Falcone, 2011). Daily discharge data were obtained from the USGS National Water Information System (NWIS) gauge stations. In addition, the complete list of reservoirs (along with their main purposes) was obtained from the Global Reservoir and Dam Database (GRanD) (Lehner et al., 2011).

Using the listed criteria, a total of 178 pairs of reservoirs and gauge stations were first identified (Fig. 1 and Supplementary Table S1). The selected reservoirs were then categorized based on their main purposes, which include flood control, hydroelectricity, irrigation, water supply, and others (i.e., navigation, recreation, and fisheries). Although a majority of the reservoirs are in fact multipurpose, to focus our discussion and analysis, we only considered their main purpose as reported in the GRanD database (see Supplementary Table S1). After model evaluation and validation (described in Sections 2.3 and 3.1), we further sub-selected 138 of 178 subbasins that had better model performance to support the full analysis.

2.2. Climate projections

In this study, an ensemble of high-resolution climate projections were generated from a hybrid framework that downscaled ten general circulation models (GCMs) from Coupled Model Intercomparison Project Phase 5 (CMIP5) to 4 km spatial resolution over the CONUS. First, each of the ten GCMs was dynamically downscaled to 18 km resolution using Regional Climate Model version 4 (RegCM4) (Giorgi et al., 2012). The RegCM4 downscaling consisted of 40 years in the baseline period (1966–2005) and 40 years in the near-term future period (2011–2050) under Representative Concentration Pathway 8.5 (RCP8.5). The 10 models were selected based on the availability of GCMs with three-dimensional atmospheric fields at a sub-daily timescale, which is necessary for dynamical downscaling. These ensemble members are: ACCESS1-0, BCC-CSM1-1, CCSM4, CMCC-CM, FGOALS-G2, IPSL-CM5A-LR, MIROC5, MPI-ESM-MR, MRI-CGCM3, and Nor-ESM1-M. Although this study selected a ten-member ensemble for climate projections, projected changes in precipitation and temperature in the ensemble members do not exhibit obvious bias in any one direction compared with climate projections from 97 CMIP5 GCMs under four emission scenarios (RCPs 2.6, 4.5, 6.0, and 8.5) (Brekke et al., 2014; Fig. 2).

The results from these RegCM4 simulations were further spatially interpolated and statistically bias corrected to the targeted 1/24° (~4 km) geographical grid using a quantile-based bias correction method (Ashfaq et al., 2010, 2013, 2016). The 1/24° (~4 km) resolution 1966–2005 monthly precipitation and temperature values from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) (Daly et al., 2008) were used as the historic observation for bias correction. The results of these RegCM4 simulations are detailed in Ashfaq et al. (2016).

2.3. Hydrologic model simulations

The VIC hydrologic model (version 4.1.1) (Liang et al., 1994, 1996; Cherkauer et al., 2003) was used to simulate streamflow based on the observed and projected meteorological forcing. We used a calibrated VIC model implementation at a 1/24° (~4 km) resolution for the entire CONUS with a 3-h time step. Oubeidillah et al. (2014) and Naz et al. (2016) provide a detailed description of the VIC model setup, parameters, and results. For model calibra-

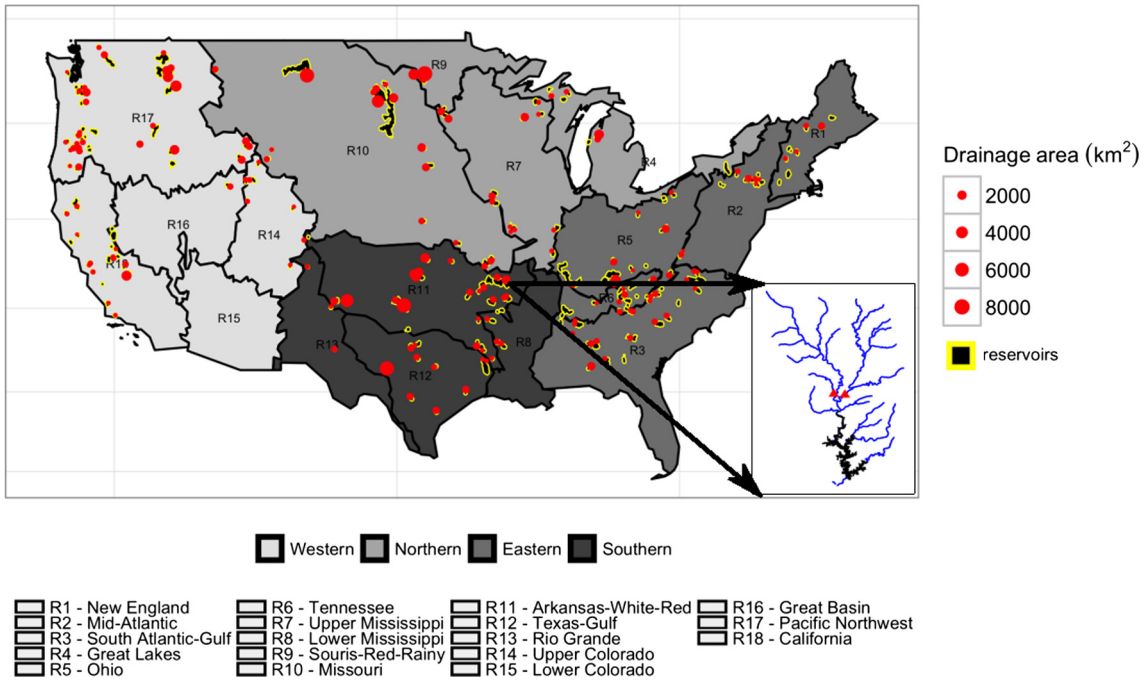

Fig. 1. Study area showing the location of 178 gauges above reservoirs within 18 two-digit hydrologic regions (HUC2). The shaded areas represent the four regions included in the study, and the numbers represent HUC2 identification codes. The size of each circle represents the drainage area of the gauge station from USGS NWIS. The inset provides a closeup of two USGS gauge locations upstream of Northfork Lake reservoir as an example.

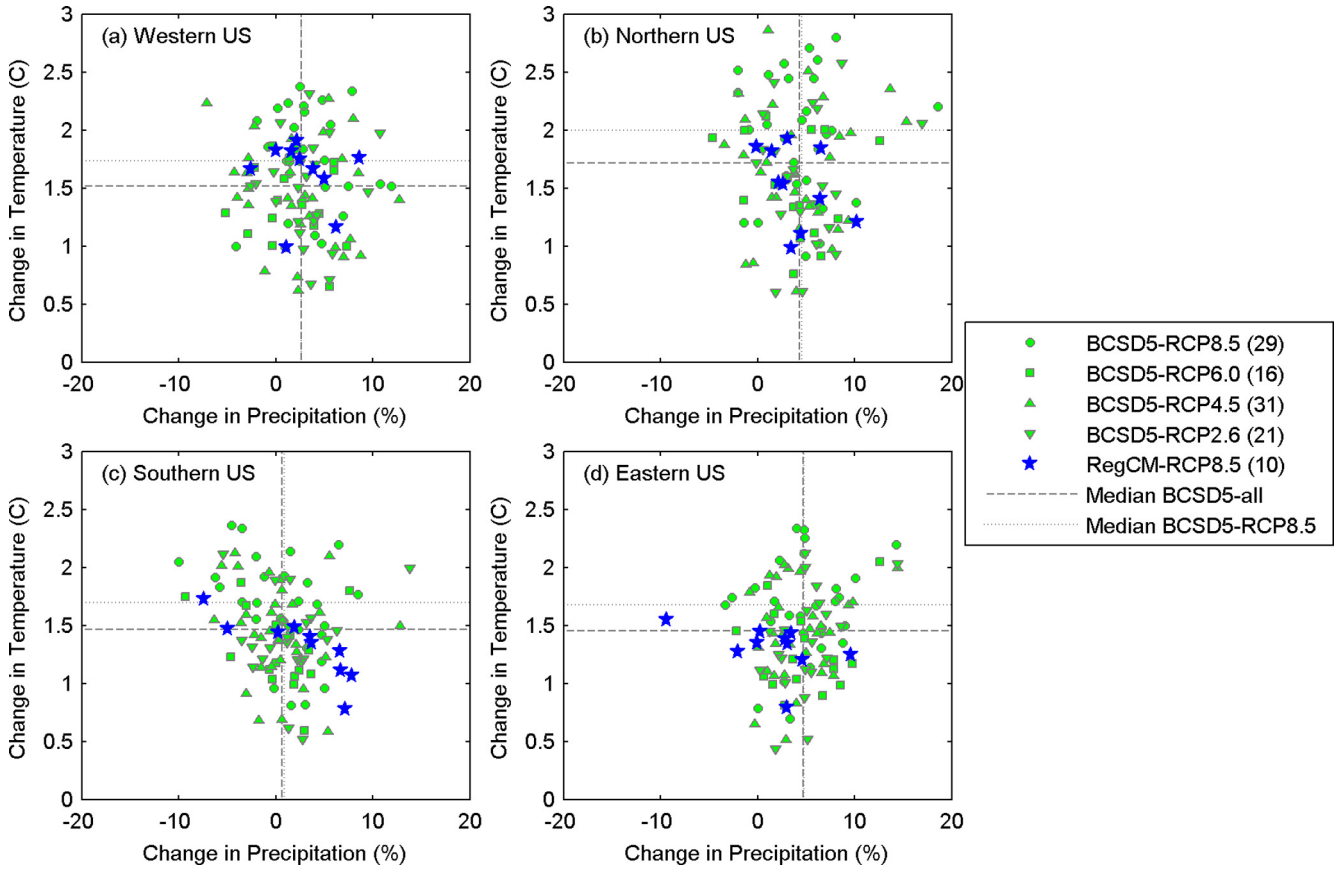

Fig. 2. Scatter plots of annual temperature and precipitation changes for 97 statistically downscaled CMIP5 Global Climate Model projections under four emission scenarios (RCP 2.6, 4.5, 6.0, and 8.5; green symbols) plotted against the ten RegCM4 simulations (blue symbols) selected for this study. Change is defined as the degree change of national average temperature (°C) and percentage change in national average precipitation (%) from the 1966–2005 baseline to the 2011–2050 future periods. The 97 climate projections were obtained from the bias-correction spatial disaggregation (BCSD) data archive (Brekke et al., 2014).

tion and validation, Oubeidillah et al. (2014) used the simulated monthly VIC total runoff (i.e., surface runoff plus baseline) by the USGS WaterWatch runoff data set (Brakebill et al., 2011) at each of the 2107 USGS eight-digit hydrologic subbasins (HUC8) across the CONUS. Driven by the gridded 1980–2012 CONUS temperature and precipitation observations from Daymet (Thornton et al., 1997) and PRISM (Daly et al., 2008) and the reanalyzed surface wind speeds from the North American Regional Reanalysis (Mesinger et al., 2006), VIC model version 4.1.1 was executed in the full energy mode in which the model iteratively solves the energy and water balances at a 3-h time step. To manage the large amount of data (i.e., around half a million grid points in the US), all forcing, soil, vegetation, global parameter, and output flux files are organized according to the HUC8 subbasins. The calibrated VIC model simulations are hereinafter referred to as "control-run" simulation.

To simulate future hydrological response to climate change, the daily bias-corrected RegCM4 outputs (i.e. daily minimum and maximum temperature and daily precipitation) were used to drive the calibrated VIC model. To run the model at a 3-hourly time step, the daily precipitation data were temporally disaggregated by equally apportioning days to 3-hourly intervals. Temperature, humidity, downward short and long-wave radiation data were derived at 3-hourly intervals from the daily temperature range and daily total precipitation using methods described in Bohn et al. (2013). However, previous studies have found that this approach could result in relative humidity trends opposite to those in the driving GCMs, thus affecting the simulated runoff (Bohn et al., 2013; Pierce et al., 2013). In order to ensure that the VIC model did not significantly alter the projected trends by RegCM4, we compared the regionally averaged projected changes (future minus baseline) in annual net shortwave radiation, net longwave radiation, relative humidity, and specific humidity between the RegCM4 and VIC model (not shown here) for the four US mega regions. The trends of humidity (particularly relative humidity) were generally consistent between the RegCM4 and VIC model. However, small differences between the VIC and RegCM4 simulated shortwave and longwave radiation changes were found (i.e. up to 2%). Therefore, we do not expect significant impact of these differences on the simulated hydrological response by the VIC model.

To simulate the daily transport of runoff and drainage to the channels, the simulated daily surface runoff and baseflow from each grid cell were routed to the 178 gauge locations through the river network using a linear reservoir model based on Lohmann et al. (1998). The most important routing parameter, flow direction grid, was developed using both National Elevation Dataset (Gesch et al., 2002) and the National Hydrography Dataset Plus (EPA, 2010). While the flow directions can be derived through standard geographic information system software packages (e.g., ArcHydro; Maidment, 2002), the process could result in river networks inconsistent with the observed ones (i.e., from NHDPlus) in flat areas and in closed inland basins. To avoid this issue, we derived the flow direction grids separately for each HUC8 using a river burn-in technique. Before calculating flow directions through conventional methods, we artificially lowered the elevations of grids that are overlapped with NHDPlus rivers. The derived flow direction grids were then inspected for inconsistencies between simulated and observed river networks. As an example, Fig. 3 shows comparison of delineated river network derived from 1/24° digital elevation model with NHDPlus rivers for two selected USGS gauges (red triangles) upstream of Northfork Lake reservoirs. While the computed flow direction grids could reasonably depict the relatively large river networks in the east, they often failed to represent relatively small river networks upstream of the gauge stations. In such cases, the flow direction grids were manually adjusted to ensure agreement between simulated and observed river networks. Overall, the mean absolute percentage difference and R^2 value between the USGS reported drainage areas and the VIC modeled drainage areas for the 178 subbasins were 9% and 0.99, respectively.

Although the high-resolution 1/24° VIC model grid improved the delineation of the river networks (compared with other commonly used 1/8° VIC model applications), the grid resolution may still be insufficient to model streamflow for small drainage areas. Therefore, we opted to focus only on locations with upstream drainage areas greater than 100 km^2. To further enhance the performance of runoff routing at a finer spatial scale, a non-grid–based routing model, such as the Routing Application for Parallel Computation of Discharge (David et al., 2011), may be a promising alternative.

2.4. Analysis

To investigate the projected change of reservoir inflows, we used four indices:

(1) **Q** – the mean annual streamflow.
(2) **CT** – the annual center timing of streamflow. For a given water year (October 1st–September 30th), CT (Stewart et al., 2005) represents the date since October 1st at which 50% of the total streamflow mass occurred.
(3) **Q100** – the 100-year return level of daily high streamflow, which is used as a proxy for the likelihood of flooding.
(4) **7Q10** – the 10-year return level of 7-day average low streamflow, which is used as a proxy for droughts.

All analyses were conducted separately for each of the ten ensemble members in the baseline and future periods for all selected locations. To estimate both Q100 and 7Q10, the annual maximum daily streamflow and annual minimum 7-day average streamflow were first summarized and fitted separately into the generalized extreme value (GEV) distribution using the L-moments method (Wang, 1997; Hosking and Wallis, 1993). The Kolmogorov-Smirnov test (Chakravarti et al., 1967) was then used to examine the goodness-of-fit of the GEV.

The results of these analyses were used to calculate the percentage change ([future minus baseline]/baseline) in projected annual flow (Q), high streamflow (Q100), low streamflow (7Q10), and change (future minus baseline) in streamflow timing (CT) for each ensemble member. To evaluate the effects of hydrologic extremes on reservoir storage, changes in the selected subbasins were also summarized by the reservoirs' main usage. Additionally, the multi-model uncertainty for the simulated results was also examined to understand the robustness of simulated changes across all ensemble members.

3. Results and discussion

3.1. Hydrologic model validation

For the period of 1981–2012, we evaluated the simulated streamflow at each selected gauge location using USGS streamflow observations. The observed versus simulated annual average streamflow are illustrated in Fig. 4(a) and (b). The monthly coefficient of determination (R^2) and Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe, 1970) values between observed and simulated streamflow are shown in Fig. 4(c) and (d). The daily R^2 and NSE at 84 stations with complete historic records are shown in Fig. 4 (e) and (f).

In general, the VIC annual streamflows closely matched the observed ones for many basins across the US. Monthly coefficient values ranged from 0.2 to 0.9 with 65% of subbasins (116) having

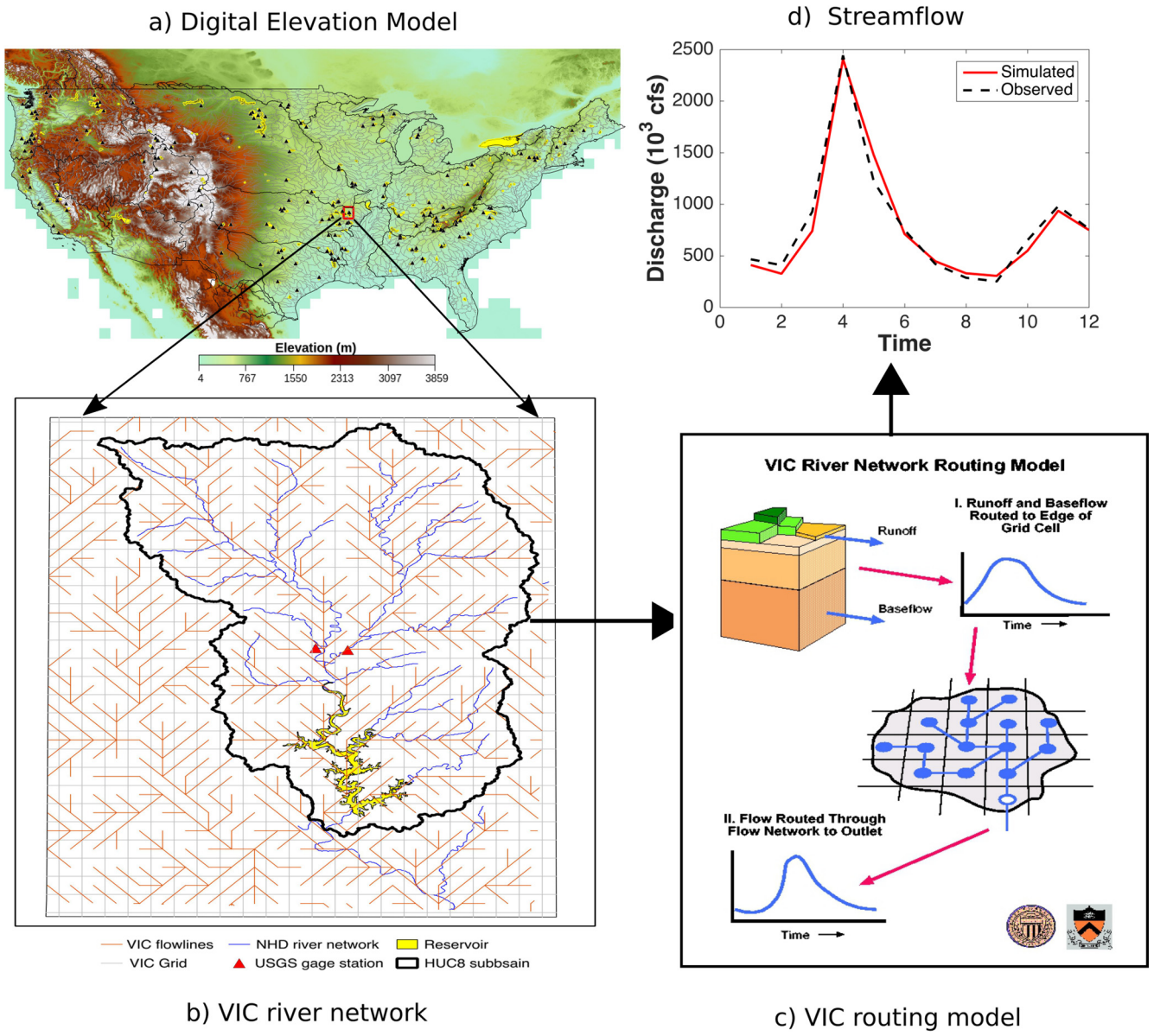

Fig. 3. Routing modeling framework. (a) Digital elevation model at 1/24° grid cell used in the routing of streamflow, (b) an example of an HUC8 subbasin river network from a 1/24° digital elevation model with two USGS gauges upstream of Northfork Lake reservoir, (c) a schematic of the VIC routing model (Adam et al., 2007), and (d) an example of simulated annual streamflow.

a NSE greater than 0.5. About 81% percent of the subbasins (145) had a R^2 greater than 0.5 (Fig. 4c and d). At the daily time scale, the VIC model also indicated acceptable performance with NSE and R^2 values both ranged from 0.1 to 0.8 for the selected subbasins. In the eastern US (New England, Mid-Atlantic, South Atlantic-Gulf, Ohio Valley, and Tennessee) and across the western US (Colorado, Great Basin, Pacific Northwest, and California), the VIC modeled streamflow results are in good agreement with the observed streamflow at both daily and monthly time scales. However, in the central US (Missouri, Arkansas-White-Red, and Texas), the VIC model performance was relatively low for both monthly and daily streamflow with a R^2 of approximately 0.4 and an NSE between 0.2 and 0.4. Previous studies that applied hydrologic modeling across the CONUS have also shown poor model performance in arid regions and generally better performance in the eastern and western US (Newman et al., 2015; Clark et al., 2008; Martinez and Gupta, 2010). The low performance of the model in the central US can be attributed to uncertainties from atmospheric forcing data, static input data (e.g., soil and land cover types), or inherent model limitations. For example, Naz et al., 2016 showed improved runoff simulations after bias correction of forcing data with PRISM dataset and adjustment of vegetation and soil parameterizations.

Furthermore, it is challenging for the land surface models to correctly represent the saturation excess runoff in arid to semi-arid regions. In such areas, low runoff observations may induce low values of the infiltration parameters during calibration, which may prevent the accurate simulation of runoff peak flows, resulting in lower NSE values. The density of precipitation and streamflow gauges is also relatively low in the central US, which makes model calibration and validation more challenging in this region.

Note that the calibration of VIC model provided by Oubeidillah et al. (2014) was carried out at the HUC8 scale using WaterWatch monthly runoff data. It was not evaluated for hydrologic extremes at daily time scale because of the unavailability of daily-resolution CONUS runoff observations. Nevertheless, earlier studies using VIC model (calibrated at monthly time scale) have been shown to suc-

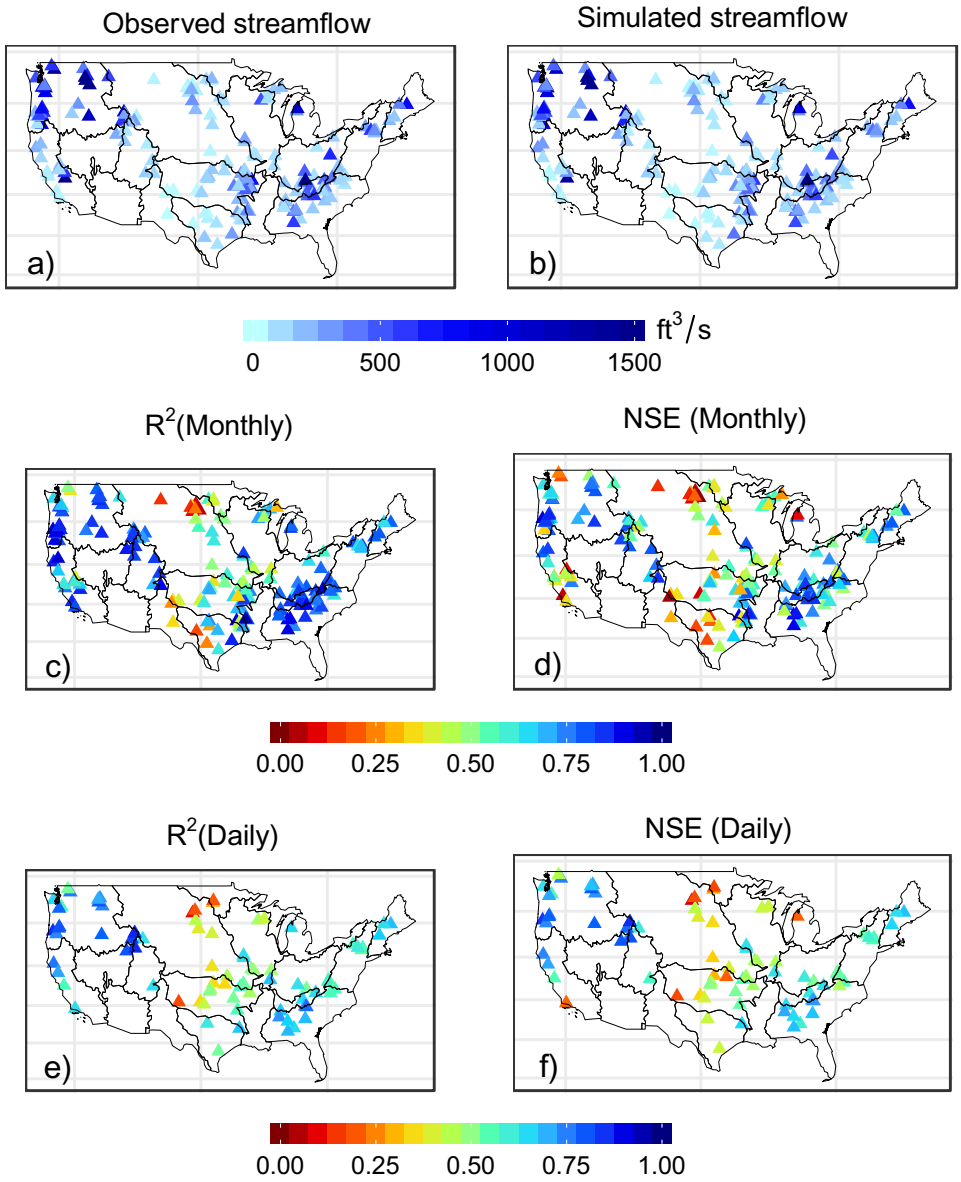

Fig. 4. The VIC model performance at each selected gauge during 1981–2012. The observed versus simulated annual streamflows are illustrated in panels (a) and (b). The monthly R^2 and NSE values between observed and simulated streamflow are shown in (c) and (d). The daily R^2 and NSE of 84 stations with complete historic records are shown in (e) and (f).

cessfully reproduce the ratio of Q100 to the mean annual flood for different climatic conditions in the western US (e.g., Hamlet and Lettenmaier, 2007). Moreover, this study mainly focuses on the percentage changes (instead of absolute projections), which is shown to be relatively less sensitive to model calibration and other possible sources of hydrologic model biases (Tohver et al., 2014; Salathé et al., 2014). Given the modeling limitations, we analyzed only the results for 138 basins where monthly NSE values were greater than 0.4 in the following sections.

3.2. Changes in inflow volume and timing

Fig. 5 shows the projected changes in streamflow volume and timing for the selected 138 reservoir inflow locations across the CONUS. The projected multi-model median annual volume showed an average increase of 4.5% for the 2011–2050 future period relative to the 1966–2005 baseline period (Fig. 5a). However, the change is spatially heterogeneous across the US. At the annual timescale, the most pronounced change was an increase (10–25%) in Q in the central US (Upper Mississippi, Missouri, Arkansas-White-Red and Texas-Gulf) and to a lesser degree in the Great Lakes, Ohio Valley, and south Atlantic-Gulf regions (1–7%) (Fig. 5a and Table 1). Compared to the eastern and central US, flows in the western US were mostly projected to decrease. On average, 17 of 29 basins exhibit a −3% decrease in Q in the Pacific Northwest region, and 7 of 8 locations exhibit a −5% decrease in Q in the California region (Table 1). Overall, the majority of ensemble members agree on the direction of change in Q (Fig. 6a).

Analyses of CT showed that, on average, the center of mass of streamflow was projected to arrive earlier by 4 days for 73% of the basins (101 of 138, Table 1). Earlier streamflow was more pronounced in the western US (i.e., 4–14 days earlier, Table 1 and Fig. 5b). CT was also projected to arrive earlier by 1–4 days for basins in the Missouri, Upper Mississippi, Great Lakes, and New England regions. In contrast, CT in the southeastern US was projected to arrive later (Fig. 5b), particularly in the Texas-Gulf region,

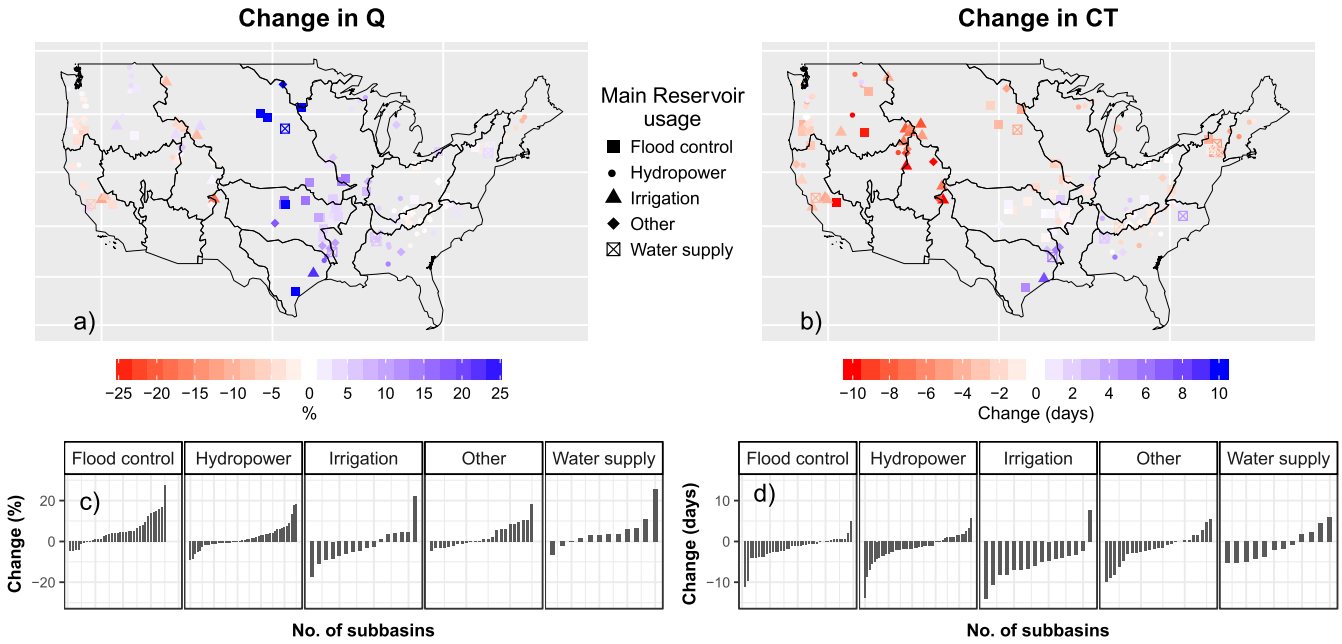

Fig. 5. The projected ensemble median change in (a) Q (%) and (b) CT (days) from the 1966–2005 baseline to the 2011–2050 future periods. The bar charts in (c) and (d) summarize the projected changes at 138 locations by the main reservoir usage. Symbols in (a) and (b) indicate main uses of reservoirs downstream of selected basins. The reservoir uses for the category "others" include navigation, recreation, and fisheries.

Table 1
The ensemble median projections of Q and CT for the 138 basins summarized by HUC2 hydrologic regions. The average change and the number of subbasins showing positive/negative change are reported.

HUC2 ID and region name	# of basins	Increasing Q (% and #)	Decreasing Q (% and #)	Later CT (days & #)	Earlier CT (days & #)
1 – New England	4	NA*	−6.22(4)	NA	4(4)
2 – Mid-Atlantic	8	1.72(6)	−1.42(2)	NA	3(8)
3 – South Atlantic-Gulf	20	5.36(13)	−0.72(7)	2(10)	2(10)
4 – Great Lakes	2	7.49(2)	NA	NA	3(2)
5 – Ohio Valley	10	2.77(7)	−0.62(3)	1(6)	1(4)
6 – Tennessee	6	2.65(2)	−1.40(4)	NA	1(6)
7 – Upper Mississippi	9	15.36(9)	NA	2(1)	3(8)
8 – Lower Mississippi	3	8.29(3)	NA	4(3)	NA
9 – Souris-Red-Rainy	0	NA	NA	NA	NA
10 – Missouri	11	16.45(9)	−8.69(2)	2(1)	3(10)
11 – Arkansas-White-Red	16	10.08(16)	NA	2(8)	1(8)
12 – Texas-Gulf	4	22.62(4)	NA	3(9)	NA
13 – Rio Grande	1	NA	−17.52(1)	3(1)	9(1)
14 – Upper Colorado	6	2.38(4)	−1.65(2)	NA	9(6)
1 5– Lower Colorado	NA	NA	NA	NA	NA
16 – Great Basin	1	NA	−5.30(1)	NA	9(1)
17 – Pacific Northwest	29	2.55(12)	−3.31(17)	1(4)	4(25)
18 – California	8	4.17(1)	−5.18(7)	NA	4(8)
CONUS	138	12.46(88)	−3.65(50)	2(37)	4(1 0 1)

* NA indicates no data.

where a 2–6 day delay was projected. However, the degree of consensus among models is low; therefore, greater uncertainty exists in the direction of change in CT projections (Fig. 6b).

The changes in streamflow volume and shifts in streamflow timing will likely affect water availability in the reservoirs. Fig. 5c and d present the changes in Q and CT for all basins grouped by main reservoir use. The results showed that the streamflow increases are likely to influence the inflows to the flood control and water supply reservoirs. For instance, 85% of basins that are upstream of flood control and water supply reservoirs were projected to receive increased annual streamflow (Fig. 5c) and earlier CT (Fig. 5d). Similarly, Q was also projected to increase in 52% of basins upstream of hydropower reservoirs (Fig. 5c), mostly located in the southern Atlantic-Gulf, Tennessee, and Ohio Valley regions. In contrast to the eastern and central US, Q was projected to decrease in the western US basins, where irrigation and hydropower are the main reservoir purposes. In those regions, 61% and 47% of basins that are upstream of irrigation and hydropower reservoirs, respectively, showed a decrease in Q. In addition to the decrease in streamflow volume, the headwater basins in the western US showed pronounced earlier CT (up to 14 days), particularly for reservoirs that are used for irrigation (Fig. 5d).

3.3. Changes in hydrological extremes

Fig. 7 shows ensemble median changes in Q100 and 7Q10 for each selected location. An increase in Q100 implies a higher probability of flood, whereas a decrease in 7Q10 implies higher proba-

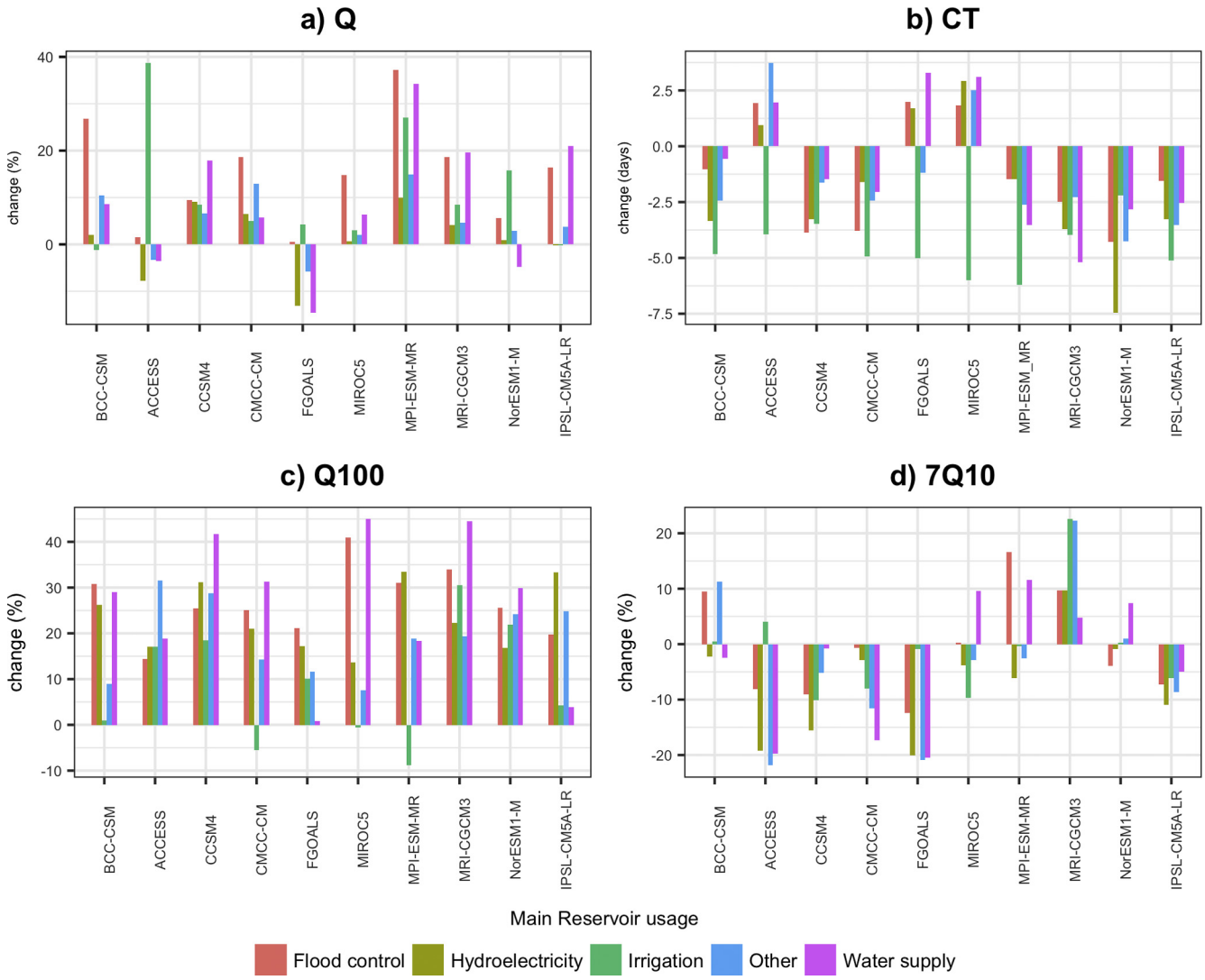

Fig. 6. The projected mean percentage change in (a) annual streamflow and (b) streamflow timing, (c) low flows (7Q10) and (d) 100 year flood magnitude (Q100) for all subbasins across 10 CMIP5 models in 2011–2050 future period. Colors in (a)–(d) indicate the main uses of reservoirs downstream of selected basins. The reservoir uses for the category "others" include navigation, recreation, and fisheries.

bility of drought. Our results indicate a robust increase in the magnitude of Q100 for nearly all locations—the strongest increases (up to 70%) are projected in subbasins across the central and eastern US (Fig. 7a)—and relatively low uncertainty across the ensemble members, as all models agree on the direction of change for all categories of reservoirs (Fig. 6c). Among different reservoir types, Q100 was projected to increase by 44% on average for basins that are upstream of flood control reservoirs (Table 2, Fig. 7c). Similarly, most basins upstream of hydropower reservoirs across the eastern US exhibit an increase in Q100 (35%, Table 2, Fig. 7a).

For 7Q10, a strong reduction (up to −40%) was projected in most basins across the eastern US (Fig. 7b). In contrast, most basins across the central US showed increases in low flows (+5 to +50%), with the exception of some basins located in the Great Lakes and Ohio Valley regions that projected decreases of up to −15% in 7Q10 (Fig. 7b). Increases in low streamflow in the central US were more likely to be caused by higher subsurface storage in the summer season, driven by increases in projected precipitation throughout the year (Naz et al., 2016). However, 7Q10 exhibited higher uncertainty, as the degree of consensus among CMIP5 models was low (i.e., only half of the models projected decreases) (Fig. 6d).

Examination of the changes in 7Q10 with respect to reservoir use suggests that projected changes in 7Q10 were more severe in the headwater basins upstream of the hydropower reservoirs (i.e., 33 of 46 subbasins showed decreasing 7Q10 by up to −11%; Table 2 and Fig. 7d). However, results were mixed for basins upstream of the flood control reservoirs, with increasing 7Q10 (up to 27%) in the central US and decreasing 7Q10 in the western US and along the lower Mississippi River (Table 2 and Fig. 7d). For basins upstream of irrigation, water supply, and other reservoirs, 7Q10 was projected to decrease (from −9 to −20%; Table 2), with more notable decreases across the California, Upper Colorado, Mid-Atlantic, Tennessee, and Ohio Valley regions.

3.4. Limitations and uncertainties

There are multiple sources of uncertainty in high-resolution future hydro-climate projections, including emission scenario, GCMs structure, GCMs initial condition, downscaling approach, and hydrologic model structure and parameters (Chen et al., 2011; Kay et al., 2009; Wu et al., 2015; Zhao et al., 2016a). In this study, we utilized dynamically downscaled multi-member regional hydro-climate projections over the CONUS (Ashfaq et al.,

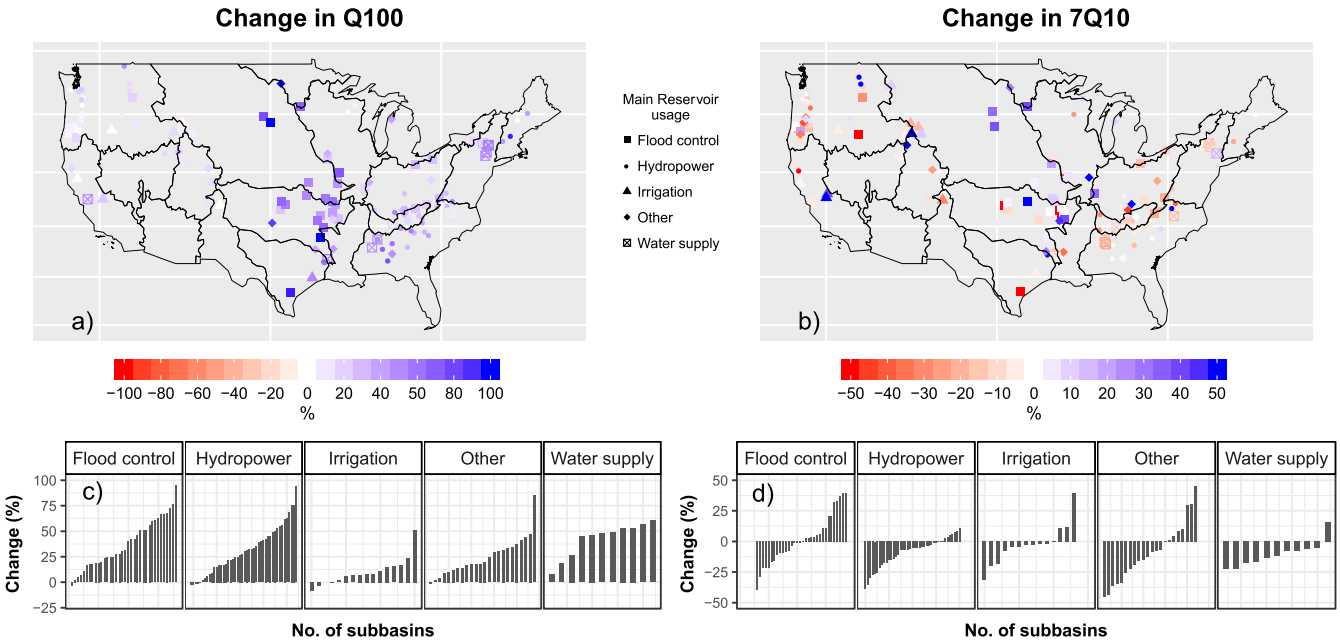

Fig. 7. The projected ensemble median change in (a) Q100 (%) and (b) 7Q10 (%) from the 1966–2005 baseline to the 2011–2050 future periods. The bar charts in (c) and (d) summarize the projected change at 138 basins by the main reservoir uses. Symbols in (a) and (b) indicate main uses of reservoirs downstream of selected basins. The reservoir uses for the category "others" include navigation, recreation, and fisheries.

Table 2
The ensemble median projections of Q100 and 7Q10 for the 138 basins summarized by main reservoir uses. The average change and the number of basin showing positive/negative change are reported. NA indicates no data.

Main reservoir usage	# of basins	Increasing Q100	Decreasing Q100	Increasing 7Q10	Decreasing 7Q10
		(% & #)	(% & #)	(% & #)	(% &#)
Flood control	38	44.8 (38)	NA	27.6 (17)	−11.6 (21)
Hydroelectricity	46	35.8 (41)	−1.5 (5)	6.2 (13)	−11.4 (33)
Irrigation	16	12.28 (14)	−5.8 (2)	15.7 (6)	−9.4 (10)
Water supply	11	42.2 (11)	NA	22.4 (2)	−20.5 (9)
Others*	25	29.7 (24)	−1.5 (1)	21.6 (12)	−15.2 (13)

* The reservoir uses for the category "others" include navigation, recreation, and fisheries.

2016), which is helpful in resolving some of the challenges that are associated with the GCMs, however, we acknowledge that a number of uncertainties still exist that may have an influence on the simulated hydrological response. For instance, use of a single regional climate model (RCM) underrepresents the uncertainty associated with the RCM's internal variability (Giorgi and Gutowski, 2015). Similarly, choice of a different downscaling approach (e.g., using statistical downscaling) and/or a different hydrologic model may influence results at specific locations. Therefore, results in this study are intended to provide overall and regional trends across a large number of subbasins in the CONUS rather than getting a precise prediction at a specific location.

Within the scope of this study, we further note that in the rain-dominated regions, the uncertainties in simulated hydrologic extremes are driven by the uncertainties in the mean and extreme precipitation projections across RegCM4 ensemble members. Similarly, uncertainties in the temperature projections across RegCM4 ensemble members can potentially impact the simulated response in the snow-dominated watersheds. In the snow-dominated watersheds, additional uncertainties can be introduced by the selection of snow modeling approaches (e.g., energy balance versus temperature based), which may result in different sensitivities to increasing temperature, and consequently influence extreme flows in the simulations. Therefore, it is possible that a single hydrologic model based projections (such as this study) potentially underrepresent the uncertainty associated with the projected changes in cold regions. As discussed earlier, uncertainties in this study may also attributed to the fact that the VIC model calibration was performed using monthly runoff data, and no calibration was carried out for hydrologic extremes at a fine temporal scale.

Additionally, the VIC model does not explicitly represent shallow groundwater, which may impact the model's ability to estimates drought conditions (e.g., groundwater effects can either cause the hydrologic droughts more persistent than meteorological drought or it may buffer the precipitation deficit). This limitation can potentially enhance the uncertainty in our results for those basins where interactions between surface and groundwater processes are strong (e.g., in the central US where the VIC model performance is relatively lower than the eastern and western US). Given these limitations, a detailed analysis is needed to investigate the uncertainties resulting from hydrologic modeling or climate model projections and their impact on the projected changes in hydrological extremes, which is beyond the scope of this study.

Finally, this study analyzed only changes in the headwater basins located upstream of reservoirs and did not account for the total impact of upstream water supply to reservoirs and/or contribution from upstream reservoirs. Similarly, effects of human activities on hydrological cycle and thus on extremes are ignored that can also be significant for highly managed watersheds, particular in the drier regions. Land use changes have the potential to

enhance the overall hydrologic response in the drier regions if the climate becomes much drier in the future (Zhang et al., 2016). Therefore, further studies should be conducted to incorporate combined effects of land use change and climate variability into the hydroclimate modeling framework for more reliable assessments of hydrological extremes and their impacts on reservoirs.

4. Summary and conclusions

This paper analyzes potential changes in Q, CT, 7Q10, and Q100 due to increases in radiative forcing and the implications of such changes for reservoir inflows. These projections are based on an ensemble of high-resolution simulations by the VIC model (Naz et al., 2016), forced with a ten-member ensemble of dynamically and statistically downscaled near-term regional climate projections (Ashfaq et al., 2016). Overall, projected changes in reservoir inflows in the future period (2011–2050) relative to the baseline period (1966–2005) exhibit a number of robust features:

1. For most of the headwater basins upstream of hydropower reservoirs across the western US, decreases in 7Q10 and earlier CT (4–14 days) were found. This suggests that hydroelectricity production may be reduced in the future, particularly during the summer when it is needed the most. In contrast, changes in ensemble median Q100 in subbasins across the western US were relatively small. However, increases in projected winter precipitation (Naz et al., 2016) and earlier streamflow may increase the likelihood of floods in winter and drought-like conditions in the summer. Bartos and Chester (2015) also suggest that the vulnerability of hydropower plants to droughts is extremely high in the arid and semi-arid southwestern US. Similar changes in the hydrological extremes over the western US are also reported in Pagán et al. (2016).
2. In the central US, Q100 was projected to increase in most basins, with more pronounced increases upstream of flood control (44%) and hydropower (35%) reservoirs. The storage provided by the large flood control reservoirs in the central US might be able to help reduce the impacts of high streamflow. However, projected increases in the probability of floods can be an issue for dams that are built for purposes other than flood control. On the other hand, such streamflow changes do not necessarily translate into a proportional increase in hydropower production for hydropower plants. In fact, depending on the storage capacity of a dam, a site that is projected to experience greater discharge volume could actually see lowered hydropower production as a result of more extreme high and low streamflow events (Lehner et al., 2005).
3. In the eastern US, our analysis suggests that hydropower and flood control reservoirs are vulnerable to changes in both kinds of hydrologic extremes because most locations exhibited a decrease in 7Q10 of up to −20% and an increase in Q100 of up to 65%. Unlike those in the western US, most of the reservoirs in the eastern US are within-year reservoirs (i.e., they refill and spill several times in a year) with limited storage capacity (Singh et al., 2014). Projected increases in winter precipitation, combined with earlier streamflow, suggest there is a likelihood of future flood events in the winter and drought-like conditions in the summer, which could complicate water resource management decisions (e.g., balance between flood control and hydropower generation). Additionally, expected increases in both floods and droughts can lead to an increase in streamflow variability in these regions (Singh et al., 2014), which could make reservoirs in the eastern US more vulnerable to projected climate conditions.

Despite the limitations as discussed above, the results showed in this paper should be beneficial for establishing future water management practices and strategies to adequately address climate change effect. For example, currently, most dams in the western US control floods in winter, store water from much of the spring snowmelt, and release water to meet summer demand. If the amount and timing of streamflow is altered as a result of climate change, as shown in this study, the existing reservoir operation rules will need to be revised (Brekke et al., 2009). A future extension can potentially look at the storage capacity in relation to the impacts identified in this study. The proposed modeling framework can be further refined by combining more predictive water resource management models (Zhao et al., 2016b; Voisin et al., 2013) into a high-resolution large-scale modeling system that can be used to investigate the combined effects of climate impacts and water management on downstream discharge.

Acknowledgments

This study was supported by the U.S. Department of Energy (DOE) Water Power Technologies Office as a part of the SECURE Water Act Section 9505 Assessment, and used resources of the Oak Ridge Leadership Computing Facility at Oak Ridge National Laboratory (ORNL). Huilin Gao was supported by the U.S. National Science Foundation grant CBET-1454297. The ORNL authors are employees of UT-Battelle, LLC, under contract DE-AC05-00OR22725 with DOE. Accordingly, the publisher, by accepting the article for publication, acknowledges that the United States government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States government purposes.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhydrol.2017.11.027.

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